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Procedia Engineering 97 (2014) 1609 – 1617

Procedia Engineering

www.elsevier.com/locate/procedia

12th GLOBAL CONGRESS ON MANUFACTURING AND MANAGEMENT, GCMM 2014

Modelling the WEDM Process Parameters for Cryogenic Treated D-2 Tool Steel by integrated RSM and GA

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Abstract

Wire electric discharge machine (WEDM) is a thermo-electric spark erosion machining process to cut very hard conductive material with the help of a wire electrode. Cryogenic treated high carbon high chromium tool steel (D-2 tool steel) is used for the current investigation. Cryogenic treatment is a surface process in which the material is placed in nitrogen environment (below -190 C) to remove stress and enhance wear resistance. The purpose of this study is to investigate the effect of parameters on surface roughness for WEDM. D-2 tool steel is used in die and punch industries, where wear takes place due to frequent operation of die-punch. To increase the wear resistance the cryogenic treated work-piece is used for the research. The Mathematical modelling of the process is carried with the help of Response surface methodology (RSM). The central composite rotatable design (CCRD) has been used to planning the experiments. The input process parameters are pulse on time, pulse off time, servo voltage and peak current. Out of which Pulse on-time has maximum effect on surface roughness as compared to other process parameters. Genetic algorithm is used to predict the best individual parameters along with the predicted fitness values.

Selection and peer-review under responsibility of the Organizing Committee of GCMM 2014

Keywords: CCRD; Cryogenic Treatment; D-2 Tool Steel; GA; Mathematical modelling; RSM; WEDM.

1. Introduction

Cryogenic treatment is the treatment of work-material to cryogenic temperatures (i.e., below –190°C) to

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Selection and peer-review under responsibility of the Organizing Committee of GCMM 2014
doi:10.1016/j.proeng.2014.12.311

remove residual stresses and improve wear resistance on steels. A wide range of applications has been found from industrial tooling to improvement of musical signal transmission. Wire cut Electrical-discharge machine (WEDM) is a spark-erosion thermo-electric non-conventional machining process to machine hard conductive metal and alloy. The main mechanism of metal removal in WEDM constitutes the erosion due to spark generated between tool (i.e. wire) and work-piece submerged in a liquid dielectric medium. The sparks generated between the gap of tool and work-piece removes the material with the help of de-ionized water, which flushes all the debris of eroded material [1-2]. WEDM is an important non-traditional manufacturing process for the tool, mould, automobile, aero-space, medical and die industries. The use of WEDM increasing day-by-day due to ability to make complex shapes with hard materials and alloys. This process consists of a number of control factors and their stochastic nature, due to which it is a challenging task to achieve optimal performance against the required response. This problem can be solved by establishing a relation between the control factors of the process and quality characteristics by design of experiments [3]. There are various researchers worked on WEDM. The work of few of them has been described in the below paragraphs.

Garg et al. [4] found the optimal set of process parameters while machining titanium 6-2-4-2 on WEDM. Box-Behnken design has been adopted for the planning of experiments. The response variables considered were cutting speed and surface roughness. Non-dominated sorting genetic algorithm-II was used to find the optimal solution. Sharma et al. [5] planned the experiments using central composite design. Pulse on-time, pulse off-time, servo-voltage, peak-current and wire-tension are the input process parameters along with cutting speed and dimensional deviation as response variables. The concept of desirability has been used for this multi-quality characteristics optimization. Khanna and Singh [6] investigated the optimal setting of control factors for cryogenic treated D-3 material on WEDM. Central Composite Designs to develop an empirical relationship between different process parameters and output responses namely Metal Removal Rate (MRR) and Surface Roughness (SR). The mathematical model so developed is analyzed and optimized to yield values of process parameters producing optimal values of output response. Gupta et al. [7] optimized the process parameters for the minimum value of kerf width. Better value of kerf width obtained at higher value of pulse on time, pulse off time, spark gap voltage and peak current and lower value of wire tension. Response surface methodology based central composite design has been used for empirical relationships. Kumar et al. [8] investigated the optimal setting of WEDM process parameters using response surface methodology for pure titanium. Machining rate, wire wear ratio, dimensional deviation and surface roughness are the response variables during their research. Jangra et al. [9] investigated the optimal setting of process parameters (i.e. taper angle, peak current, pulse on-time, pulse off-time, wire tension and dielectric flow rate) for material removal rate and surface roughness concurrently using Taguchi- grey relational analysis. Outcome proves that grey relation theory optimized process parameters successfully for multiple performance characteristics. Pasam et al. [10] investigated the WEDM of titanium alloy (Ti6Al4V). The behaviour of eight process parameters was studied using Taguchi parameter design. An attempt is made to optimize the surface roughness prediction model using Genetic Algorithm (GA). Kondayya and Krishna [11] used the non-dominated sorting genetic algorithm-II (NSGA-II) for modelling and optimization of WEDM process. Metal removal rate and surface roughness were considered as machining performance parameters. Prasad and Krishna [12] optimized the process parameters of WEDM for the response variables (metal removal rate and surface roughness) using non-dominated sorting genetic algorithm (NSGA). Along with NSGA pareto optimal set of solutions was also used for multiple-quality characteristics.

Nomenclature

T_{on}	Pulse on-time (μs)
T_{off}	Pulse off-time (μs)
SV	Spark Gap voltage (V)
IP	Peak Current (A)
SR	Surface Roughness (μm)
WEDM	Wire electric Discharge Machining
RSM	Response Surface Methodology
CCRD	Central Composite rotatable Design
ANOVA	Analysis of variance

This literature review reveals that a little research has been observed after the processing (cryogenic treatment) of work-piece. As this treatment enhance the wear resistant and the life of tool and die [13]. In this research D-2 tool steel is selected as work-piece for experimentation. To evaluate the effects of machining parameters on performance characteristics, and for planning of experiments a specially designed experimental procedure called Response Surface Methodology has been used. For the optimal sets investigation genetic algorithm is used.

2. Process Parameters of WEDM

There are a number of process parameters in WEDM, out of them significant process parameters are considered after preliminary study. The chemical composition of D-2 tool steel is given in table 1. The process parameters, their designated symbols and range are given in Table 2.

Table 1: Chemical Composition of D-2 Tool Steel

Element	C	Mn	Si	Co	Cr	Mo	V	P	Ni	Cu	S	Fe
%	1.4-1.6	0.6	0.6	1.0	11-13	0.7-1.2	1.1	.03	.3	.25	.03	Balance

Table 2: Range of Process Parameters

Parameters	Coded Factor	Symbol	Units	Lower Limit	Upper Limit
Pulse on Time	A	T_{on}	µs	105	124
Pulse off Time	B	T_{off}	µs	25	55
Servo Voltage	C	SV	V	30	80
Peak Current	D	IP	A	110	190

2.1 Cryogenic treatment

It is the process of treating material to cryogenic temperatures (i.e. below -190°C) to remove residual stresses and improve wear resistance on steels. The process has a wide range of applications from industrial tooling to improvement of musical signal transmission. The range of all the process parameters is selected for the present study based on the results obtained from preliminary experiments.

2.2 Experimental Methodology

Experiments were performed on Electronica Sprintcut wire-cut electrical discharge machine tool. During the experimentations the cutting of the work piece was done. The size of work-piece is 10mm×10mm×18mm. The work material, electrode and the other machining condition are as follows:

1. Work piece : Cryogenic Treated High Carbon High Chromium tool steel (D-2 Tool Steel)
2. Electrode (tool) : 250 µm φ, CuZn37 Master Brass wire (900 N/mm^2 tensile strength)
3. Workpiece height : 18 mm
4. Conductivity : 20 mho
5. Cutting voltage (V) : 80V
6. Die-electric temperature: 35 °C
7. Injection pressure set point was at 7 unit (105 Kg/cm^2)
8. Servo feed : 2050 units

The surface roughness is measured by Mitutoyo make surftest SJ 201P with a least count of 0.01µm. Six readings are taken then the mean value is considered. The travel of stylus for measuring the surface roughness is perpendicular to the travel of wire.

2.3 Response Surface Methodology(RSM)

RSM has been utilized for mathematical modelling in the form of multiple regression equation for the response variables of WEDM. The dependent parameters were viewed as a surface to which a mathematical model is fitted in RSM. The second order response surface has been assumed as in equation 1 for the development of regression equations related to response variable of WEDM process:

$$y = \beta_0 + \sum_{j=1}^{q} \beta_j x_j + \sum_{i=1}^{q} \beta_{jj} x_j^2 + \sum\sum_{i<j} \beta_{ij} x_i x_j + \varepsilon \tag{1}$$

This assumed surface Y contains linear, squared and cross product terms of parameters x_i's.
Wherex_i, x_j, x_q are input or independent process parameters.
β_0, β_{ii}, β_{ij} are unknown parameters or regression coefficients.
ε = Random error.

The regression coefficients can be evaluated by numerous experimental design techniques. Box and Hunter [14] suggested a method, based on central composite rotatable design, which fits the second order response surfaces very precisely.

Table 3: Design of Experiment

Std	Run	A:Ton (µs)	B:Toff (µs)	C:SV (V)	D:IP (A)	SR (µm)
1	19	124	55	80	110	2.9
2	9	124	55	30	110	1.69
3	5	124	25	80	190	3.8
4	13	105	55	30	190	1.3
5	16	124	25	30	190	2.3
6	12	105	25	80	110	2.13
7	8	105	55	80	190	1.3
8	17	105	25	30	110	1.4
9	3	98.52	40	55	150	1.92
10	7	130.48	40	55	150	4.42
11	1	114.5	14.77	55	150	2.32
12	21	114.5	65.23	55	150	2.12
13	4	114.5	40	12.96	150	1.03
14	15	114.5	40	97.04	150	2.8
15	20	114.5	40	55	82.73	2.6
16	11	114.5	40	55	217.27	1.8
17	10	114.5	40	55	150	3.12
18	14	114.5	40	55	150	2.8
19	18	114.5	40	55	150	2.8
20	6	114.5	40	55	150	2.92
21	2	114.5	40	55	150	2.82

3. Results And Discussion

The planning of experiments were carried using RSM based central composite second order rotatable design [3] for investigating SR. Design of experiment reduce the number of experimentations without loosing the accuracy of results. A total of 21 experiments were performed according to design of experiments setting the various levels of process parameters on the values given in table 3.

Table 4: Pooled ANOVA for Response Surface Reduced Quadratic Model

Source	SS	df	MS	F-Value	p-value	
Model	13.86	10	1.39	29.14	< 0.0001	**significant**
T_{on}	5.62	1	5.62	118.27	< 0.0001	
T_{off}	0.02	1	0.02	0.42	0.5313	
SV	3.01	1	3.01	63.39	< 0.0001	
IP	0.32	1	0.32	6.73	0.0268	
T_{on}×T_{off}	0.32	1	0.32	6.71	0.0269	
T_{on}×SV	0.49	1	0.49	10.3	0.0093	
T_{on}×IP	0.2	1	0.2	4.2	0.0676	
T_{off}^2	0.99	1	0.99	20.79	0.001	
SV^2	1.99	1	1.99	41.93	< 0.0001	
IP^2	1.04	1	1.04	21.95	0.0009	
Residual	0.48	10	0.048			
Lack of Fit	0.4	6	0.067	3.57	0.1194	**not significant**
Pure Error	0.075	4	0.019			
Cor Total	14.33	20				
Std. Dev.		0.22		**R-Squared**		0.9668
Mean		2.39		**Adj R-Squared**		0.9336
C.V. %		9.11		**Pred R-Squared**		0.8518
PRESS		2.12		**Adeq Precision**		19.393

3.1 Analysis of Surface Roughness

Pooled ANOVA for SR has been shown in Table 4 and it recommends that the quadratic model is statistically significant for analysis of SR. From the table it is clear that the value of R^2 and adjusted R^2 is more than 95%. This means that the model obtained can be used for future outcomes. The difference between adjusted R^2 and predicted R^2 is less than 0.20, which is good for our results.
Adequate precision is the signal to noise ratio and a value greater than 4 is desirable. Here in the ANOVA the value comes out to be 19.393, which is indication of a good model. The *p*-value for the model is lower than 0.05 which shows that the model is considered to be statistically significant. The lack-of-fit term is non-significant as it is preferred. The reduced model results indicate that the model is significant (R^2 and adjusted R^2 are 96.68% and 93.36% respectively), lack of fit is non-significant as p value is 0.119 (and significant value is less than 0.05), Figure 1and 2 displays the normal probability plot of the residuals and predicted Vs actual for SR. It is noticed that the residuals are falling on a straight line, which means that the errors are normally distributed.
While after pooling the Final Equation in Terms of Actual Factors is as follows:

$$SR=-4.36018+4.28190E\text{-}004*A+0.33666*B-0.036375*C-0.030480*D-2.17783E\text{-}003*A*B+1.04211E\text{-}003*A*C$$
$$+6.46157E\text{-}004*A*D-1.14074E\text{-}003*B^2-5.83200E\text{-}004*C^2-1.64836E\text{-}004*D^2 \quad (2)$$

The response surface gives the plot between the process parameters and the response variables. The 3D interaction plot shows the interaction between the different process parameters.

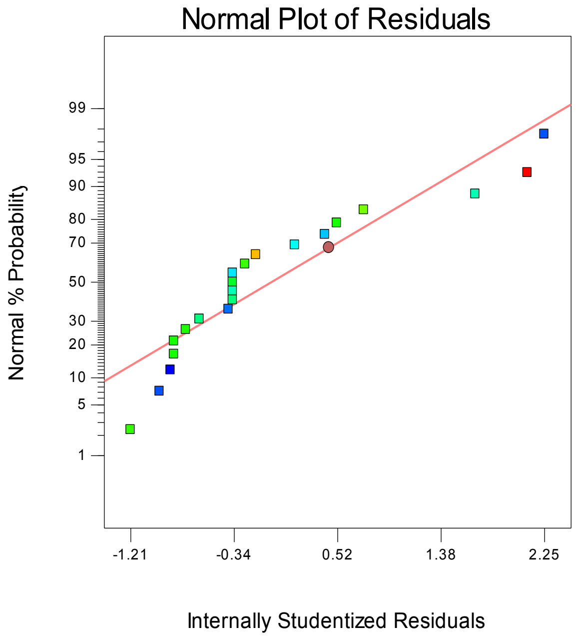

Fig. 1. Normal Plot of residuals for DD

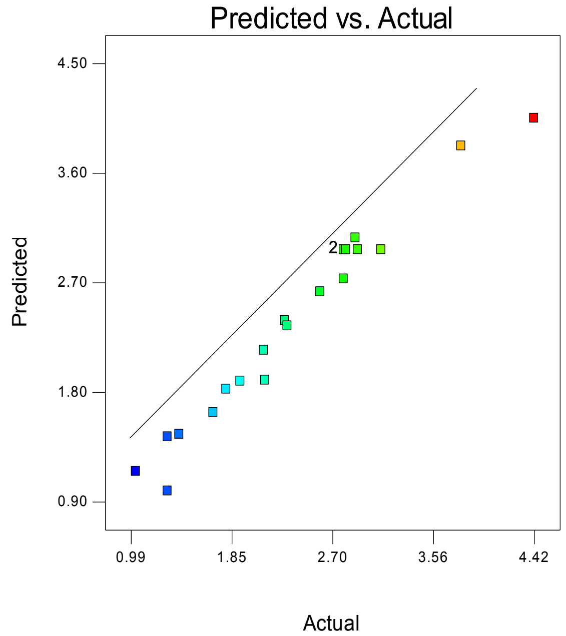

Fig.2. Plot for Predicted Vs Actual

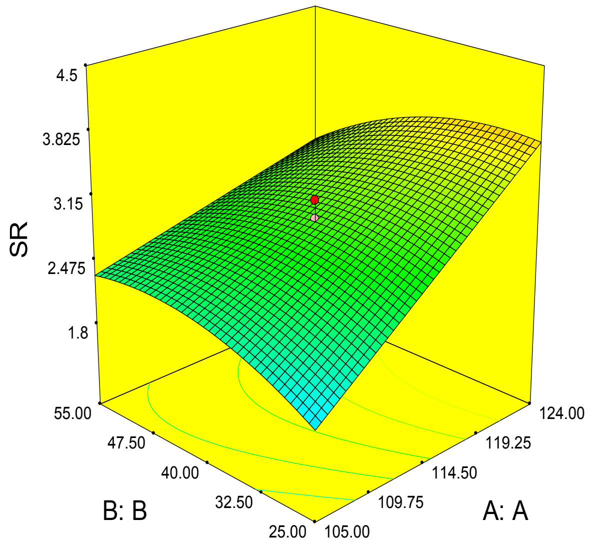

Fig. 3. Interaction Plot of Ton and Toff

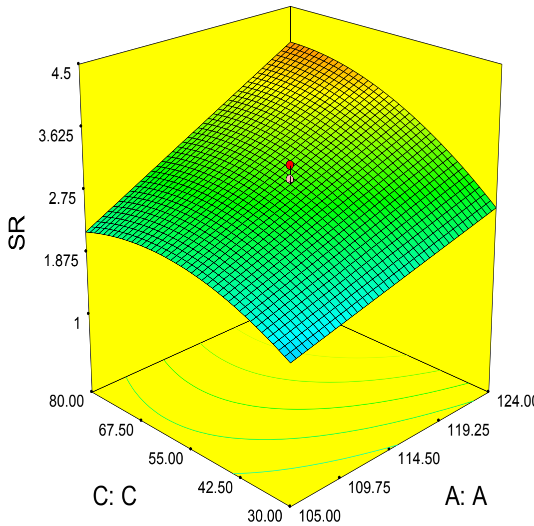

Fig.4. Interaction Plot of Ton and SV

It also explains the variation of response variable at different conditions (i.e. when one parameter is at lower value and other is varying from low to high and vice versa). Figure 3 gives a 3D interaction plot between pulse on time (T_{on}) and pulse off-time (T_{off}).Lower value of Ton favors the SR. The SR increases with increase of pulse on-time at both (i.e. lower and higher) values of Toff, while SR increases with increase of Toff at lower of Ton and decreases with increase of Toff at higher values of Ton. The reason behind this variation is that with increase of pulse on-time, the time for which current is on in a circuit increases which increases the spark energy and erosion rate of material. Due to which the depth of craters increases and finally SR observed to be high [15]. The variation of SR along the pulse off-time is due the fact at higher values of Ton the SR always high compared to lower one. But with the increase of Toff the spark energy decreases which also decrease the craters depth and a fine surface has been observed [16]. The 3D interaction plot between Ton and SV (fig 4) and Ton and IP (Fig 5) has been shown. In both figures a lower value of Ton favours the SR, which is already explained. A lower value of SV (30V) and higher value of IP (190) favours the SR i.e. at these points the surface roughness is minimum, so a good surface finish is obtained. The main reason behind this is that with the servo voltage the voltage between the spark increases which decreases the discharge energy and also SR.

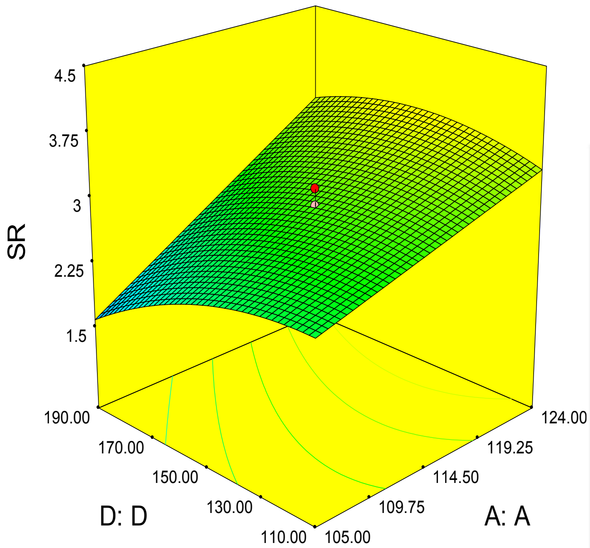

Figure 5: Interaction Plot of Ton and IP

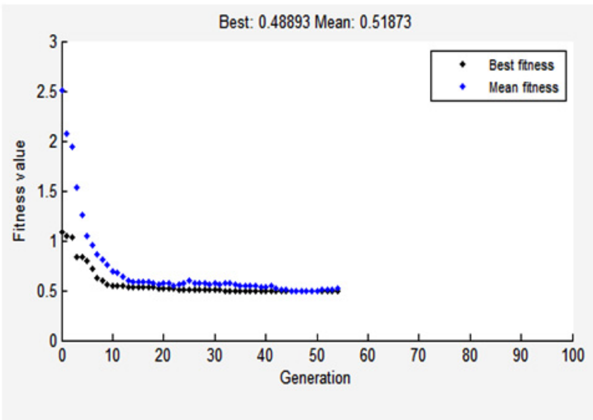

Fig .6. Best Fitness Graph

4. Genetic Algorithm

Genetic Algorithm (GA) is stochastic search methods to find the optimal solution of an optimization problem with the help of evolution function. In the early seventies Holland [17] proposed genetic algorithms as computer programs that imitate the natural evolutionary process. GA was extended by De Jong [18] to functional optimization for the optimization of a given function. Further a detailed mathematical model of a GA was presented by Goldberg [19]. Each individual in a generation (iteration) termed as chromosome shows one candidate solution to the problem. GA manipulates a *population* of individuals in each iteration. Fit individuals present in the population survive to replicate and their genetics are recombined to produce new individuals as *offsprings. Selection* provides the essential driving means for superior solutions to survive. Each solution is correlated with a *fitness* value which reflects how good it is, compared with other solutions present in the population. Crossover is the main mechanism that exchanges portions of data strings between the chromosomes with the help of recombination process. The new genetics are also introduced through *mutation* that causes random alterations of the strings. Through GA process, successively better and better individuals of the species are generated. [20], which can be observed by graphically. The optimum value is investigated depending upon the lower and upper bound of the process parameters. The range, best fitness, fitness score and best individual parameters are investigated with the help of genetic programming.

The lower and upper bound of control factors are given in equation 3 to 7 and when the objective function is optimized for the best value of SR then there are different values of selection, mutation and crossover.

$$105 \le T_{on} \le 124 \quad (3)$$

$$25 \le T_{off} \le 55 \quad (4)$$

$$30 \le SV \le 80 \quad (5)$$

$$110 \le IP \le 190 \quad (6)$$

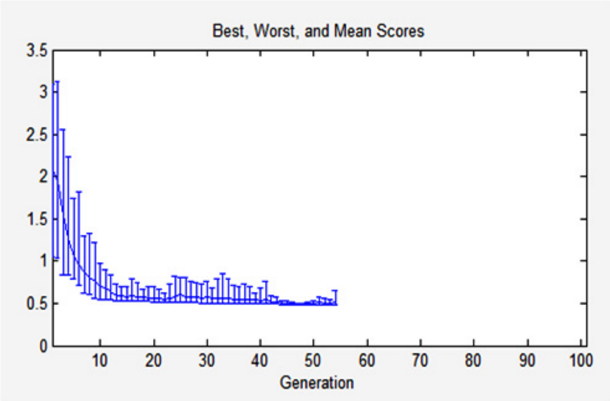

Fig .7. Best Range Graph

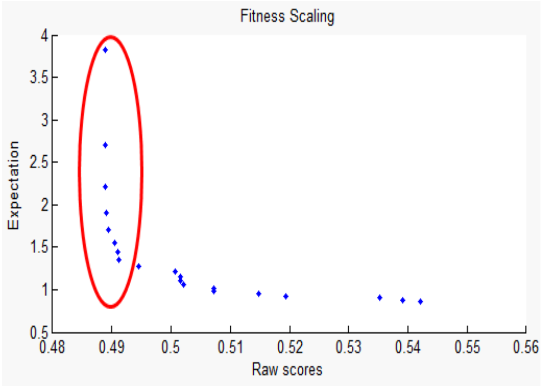

Fig .8. Fitness Scores

When the mathematical model is derived from RSM, then it is saved as a m-file in MATLAB. This m-file create a function to minimize SR with the help of that model. During the GA as optimization tool a number of possibilities were investigated at different combination of selection, cross-over fraction, mutation, cross-over and migration. It is examined that the optimized setting of genetic tool is that the Selection-stochastic uniform; Cross-overfraction- 0.6; Mutation- uniform and ratio- 0.5; Cross-over- heuristic & ratio 1.4; Migration-forward. At this optimized setting the best fitness, best range and fitness score plots are shown in Figures 6, 7 and 8 . The value of mean fitness reduces with growing number of iteration. Function tolerance was found after 55 iteration number. The ranges of these 55 iterations are given in figure 7. With the increase of number of iteration the range is found to be decreased, so with the increase of iteration in the population a better result (i.e. better species) found with the recombination. Score values are indicated in figure 8, where the best SR (0.48893 µm) is marked by red circle. In this maximum number of individuals are found.

Table 5: Best Individual for Minimum Surface Roughness

Control Factors	Symbol	Value
Pulse on Time	T_{on} (µs)	105
Pulse off time	T_{off} (µs)	25
Spark gap voltage	SV (V)	30
Peak Current	IP (A)	188

5. Concluding Remarks

Experiments were performed on WEDM using brass wire as a tool and cryogenically treated D-2 tool steel as work-piece. Numbers of experiments were reduced by central composite rotatable design. The best individual setting is given in table 5. RSM integrated with GA approach provide a systematic and effective method for the modeling and the optimization. The following conclusions are obtained from this research:

1. The increase in pulse on-time and servo voltage surface roughness increases. With the increase of peak-current the slope of surface roughness curve observed to be declined.
2. The quadratic model of SR developed by RSM gives a lot of information with a small number of experimentations. The model developed by RSM was rationally appropriate and can be used for the prediction of responses within a given limit of factors. From ANOVA it is found that pulse on time and servo voltage has the maximum percentage contribution while processing cryogenically treated D-2 tool steel as compared to pulse off time and peak current.
3. It is also concluded from the ANOVA that the model is significant. The values of R^2 and adjusted R^2 are 96.68% and 93.36% respectively and hence reproducibility of the results is good.

4. Artificial intelligence technique i.e. genetic algorithm enhance the variability in the iteration of experiments i.e. mutation, cross-over, cross-over fraction and population etc. It is used for the finding of optimum combination of independent variable for a better value of SR
5. The mean fitness and range decreases with increasing number of iterations during the genetic processing.

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